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Genetic Algorithm Based Neuro-Fuzzy Control of Thermal Power Plant (A Case Study of Savannah Sugar Power Plant)

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ABSTRACT
The accurate modeling of a nonlinear system using a Takagi-Kang-Sugeno Fuzzy Inference System requires an algorithm that can train the fuzzy inference system to minimize error(s) due to on-line data. In this research, Adaptive-Network-Based Fuzzy Inference controller is optimized with Genetic Algorithm. In a hybrid neuro-fuzzy model which is the heart of the controller, there is no guarantee that the neural network learning algorithm converges and the tuning of fuzzy inference system will be successful. The Gaussian bell (gbell) membership functions of the output of the Savannah Sugar Power Plant Boiler system, steam pressure-to-turbine parameters are optimized with genetic algorithm. Each variable has a degree of participation in every fuzzy set, based quantitatively on a membership function. The genetic algorithm is implemented in MATLAB 7.10 environment. The individual parameters are encoded as vectors of real numbers which are used for creating the Genetic Algorithm based Adaptive Neuro-Fuzzy Inference System controller. The tracking capabilities of Adaptive Neuro-Fuzzy Inference System controller and Genetic Algorithm based Adaptive Neuro-Fuzzy Inference System controller was compared, the Genetic Algorithm based Adaptive Neuro-Fuzzy Inference System controller tracking showed a better steam pressure-to-turbine stability than the Adaptive Neuro-Fuzzy Inference System controller; the robusttest of the Genetic Algorithm based Adaptive Neuro-Fuzzy Inference System controller clearly shows that the optimized controller is better suited for Savannnah Sugar Power Plant control and can be applied to similar power plants.

Keywords: Hybrid, Neuro-Fuzzy, Takagi-Kang-Sugeno, Fuzzy Inference System and Genetic Algorithm.

Introduction

The major powerful point in Adaptive Neuro-fuzzy Inference (ANFIS) systems is easy application of expert knowledge on the subject domain. However, in most cases this empirical information is not accurate enough to build an optimal system, and further proper tuning is required (Ebrahimi & Tabatabavakili (2007). If this tuning is done manually, this procedure results in numerous consultations with experts and long trial and error process, which still does not guarantee an optimal system; hence, the need for use of genetic algorithm(GA), which determine in advance (off-line) the parameters of the membership functions along each axis.

Based on the inherent characteristics of GAs, it has been suggested for numerous applications such as pattern recognition, robotics, biology, and medicine. These algorithms have also been suggested for various digital signal processing applications, for example, in adaptive estimation of time delay between sampled signals (Ebrahimi & Tabatabavakili (2007), and (Myr *et al*, (2006) fingerprint matching (Abutale & Kamel (1999) and pattern recognition(Abutale & Kamel (1999) and speech recognition (Kwong, *et al.*,1996).

This paper presents a neuro-fuzzy controller where its Gaussian bell membership function of boiler output parameters can be tuned off-line using Genetic Algorithm. The controller design approach combines the merits of fuzzy logic theory, neural networks and genetic algorithms. The proposed neuro-fuzzy network does not require a priori knowledge about the system and eliminates the need for complicated design steps like manual tuning of input-output membership functions, and selection of fuzzy rule base.

MATERIALS AND METHODS

The Savannah Sugar Company limited Numan (SSCN) thermal power plant boiler supplies 3200kPa steam pressure to a turbine which rotates the generator at 6000rpm for the production of 4.8 MW electrical power. The steam is admitted to the turbine via high pressure side through a governor regulated valve. The turbine rotor coupled to the generator by a coupling is responsible for converting steam pressure energy into mechanical energy that rotates the turbine-generator shafts for electrical power production as shown in figure 1.

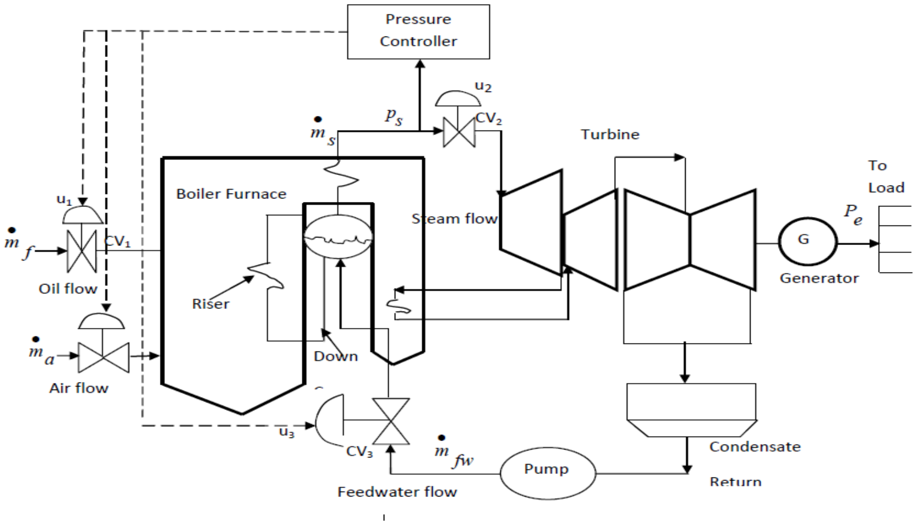

Figure 1: Schematic Diagram of SSCN Power Plant Control loops.

Genetic Based Anfis Controller Design

In this section, the development of the control strategy for control of various parameters of SSCN thermal power plant such as the oil flowrate, feedwater flowrate, and steam pressure to turbine for the generation of electrical power is presented using the concepts of GA based ANFIS controller embedded into SSCN simulink in MATLAB environment. The simulink is obtained from the SSCN thermal power plant models (Gumpy and Jiya,2013):

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$$\frac{dP_s}{dt} = 47u_1 - 0.019u_2 P_s^{\frac{9}{8}} - 0.0005u_3 - 0.4 \qquad (1)$$

$$\frac{dP_e}{dt} = \left(12u_2 - 15\right) P_s^{\frac{9}{8}} - P_e \qquad (2)$$

The control scheme diagram of plant is shown in figure 3. The Genetic algorithm (GA) is incorporated to optimize the ANFIS controller for optimal performance as shown in figure 2.

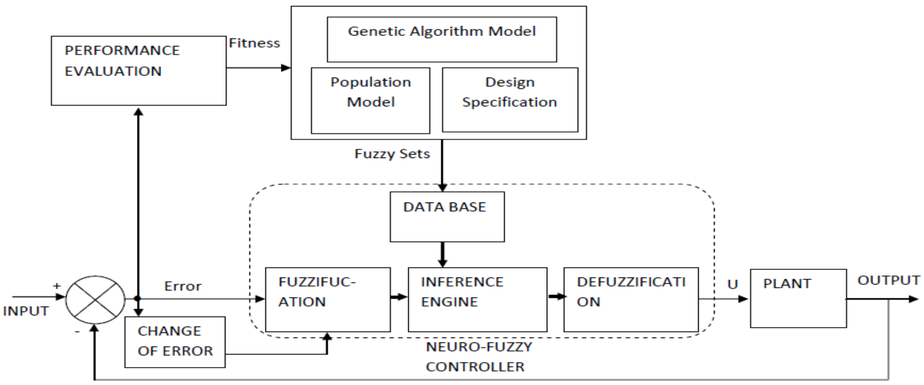

Figure 2: Genetic Tuning of Single Input Single Output Neuro-Fuzzy Controller (Mona *et al.*, 2011)

The nonlinearity of the power plant can be cancelled by using the inverted model. However, in estimating the plant model, the boiler input(s) and output with the overall power plant output forms the inputs to the controller as shown in figure 3.

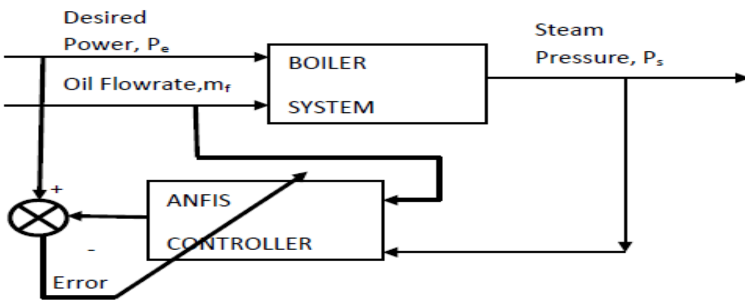

Figure 3: Block Diagram of SSCN Inverse Controller (Gumpy and Jiya, 2013)

As shown in figure 3, the plant's output data of steam pressure to turbine and electrical power forms the two input columns of the ANFIS1 and ANFIS2 controllers with the fuel flow rate and feedwater flow rate as outputs respectively, for clarity only one controller estimate is shown. The block diagram for the control of SSCN thermal power plant is shown in figure 4.

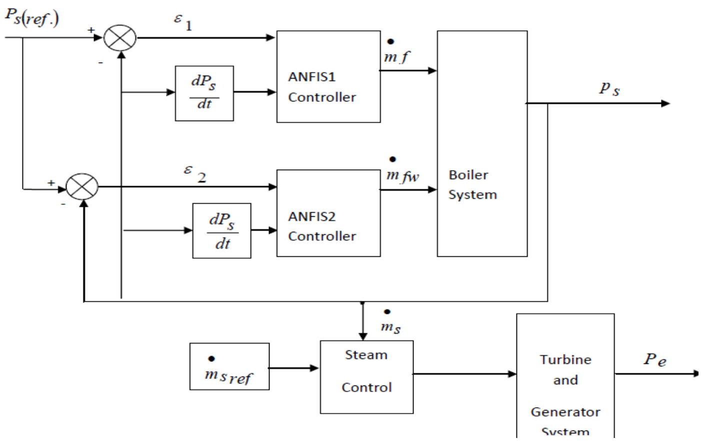

Figure 4: Block Controlled diagram of SSCN Thermal (Gumpy and Jiya, 2013)

Where

ε_1 is the first error with respect to oil flow rate,

ε_2 is the second error with respect to feed water flow rate,

$\dot{m}_f$ is oil flow rate into boiler furnace in kg/s,

$\dot{m}_{fw}$ is feed water flow rate into boiler drum in kg/s,

P_s is the boiler steam pressure to turbine in kPa,

P_e is the power plant generated electrical energy in MW.

$P_s\,(ref\,)$ is the referenced expected boiler steam to turbine steam pressure in kPa

Adaptive Neuro-Fuzzy Inference (ANFIS) Controller Design

In a hybrid Neuro-Fuzzy System (NFS), a neural network and a fuzzy system are combined into one homogeneous structure. Neural networks (NN) have strong learning capabilities at the numerical level; while fuzzy system, on the other hand, has a good capability of interpretability and can also integrate expert's knowledge. The hybridization of both the paradigms yields the capabilities of learning, good interpretation and incorporating prior knowledge Babuska, (1999).

ANFIS unit comprises of a fully connected feed forward multi-layer NN. The number of inputs to the network equals the number of state variables, and the number of neurons in the output layer equals the number of control actions applied to the system. The backpropagation training algorithm with the generalized bell activation function is employed and the weights are initialized with small random numbers. Since it is required to emphasize those actions with a better “goodness" value and de-emphasize the others with lesser credit, the learning rate is formulated as a function of the measure of “goodness “of the control action. The steepest-descent algorithm is used for modification of the weights.

ANFIS design starts with a pre-structured system; the membership function (MF) of input and output variables contains more information that NN has to drive from sampled data sets. The rules are in the linguistic forms and so intermediate results can be analyzed and interpreted easily. The modification of rules is possible during the training. Thus, combining the two methods will results in a neuro-fuzzy controller. The structure of the ANFIS is a five-layered structure illustrated in Figure 5.

The ANFIS controller based on two inputs and single output architecture is shown in figure 5

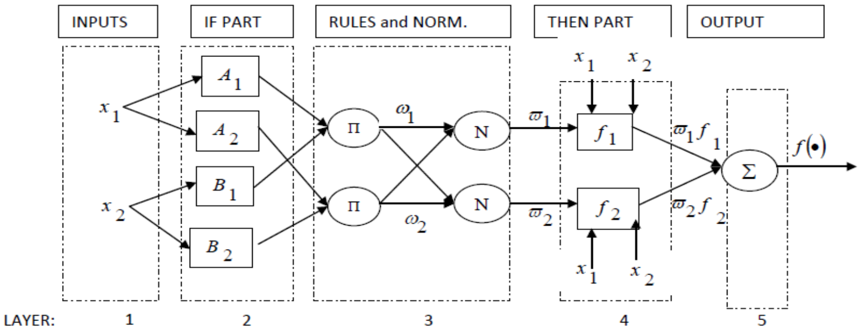

Figure 5: ANFIS Architecture Source (Jang *et el.*, 1997)

Figure 5 shows a general diagram of TSK Fuzzy model realization.

This Connectionist structure not only can house fuzzy logic rules and membership functions but also perform fuzzy inference. A typical fuzzy rule in this TSK model has the form

If x_1 is A_1 AND x_2 is B_1 , AND x_1 is A_n AND x_n is B_n Then y = f (x)

The function $y = f(x)$ is a polynomial in the input variables $x_1, x_2, \ldots, x_n$. The layer-by-layer processing of input-output data is as follows:

Layer 1: Each node is adaptive assigned a fuzzy membership value using membership functions to form a fuzzy set.

$$O_{1,i} = \mu_{A_i}(x_1) \text{ for i = 1, 2} \quad (3)$$

(23)

$$O_{1,i} = \mu_{B_{i-1}}(x_2) \quad \text{for i = 3, 4} \quad (4)$$

where

$O_{1,i}$ denotes the output of layer 1 and the *i*th node ,

$x_1 \quad x_2$ are the crisp input to node *i*,

A_i, B_i are the membership grades of the Membership functions respectively.

Layer 2: In this fixed layer, every node multiplies the input signals, denoted by " Π " and represents the rule nodes and the output $O_{2,i}$ represents the firing strength of a rule and is computed as:

$$O_{2,i} = \mu_{A_i}(x) * \mu_{B_i}(x) \tag{5}$$

Layer 3: This fixed layer consists of the averaging nodes, which is labelled as "N" and computes the normalized firing strength equal to:

$$O_i^3 = \overline{w}_i = \frac{w_i}{w_1 + w_2} \tag{6}$$

where w_i is the weight linking layer 2 to layer 3
i = 1, 2.

Layer 4: The node is adaptive and the function of this layer is to compute the contribution of each *i*th rule towards the total output and the function can be defined as:

$$O_i^4 = \overline{w}_i\, f(x_i) = \overline{w}_i \left(p_i x_1 + q_i x_2 + r_1 \right) \tag{7}$$

where
i =1and 2 for two inputs
$\overline{w}_i$ is the output weight of Layer 3 and {p_i, q_i, r_i} is the output or consequent linear parameter set.

Layer 5: This layer has a fixed single output node, which computes overall output of the ANFIS as:

$$O_i^5 = \sum_i \overline{w} f\left(x_i\right) \tag{8}$$

$$= \frac{\sum_i w_i \, f(x_i)}{\sum_i w_i}$$

The computation of these parameters (or their adjustment) is facilitated by a gradient vector, which provides a measure of how well the fuzzy inference system is modeling the input/output data for a given set of parameters.

Input variables are represented by membership functions in antecedent part. The process of obtaining values of the inputs and finding the numeric representation values of membership functions is defined as fuzzification process (Reid, & Renshaw, 1971; Kurosh, 2006 & Luis, 1994).

ANFIS Inverse Model Control Law

Generally, it is difficult to find the inverse function, f^{-1} in an analytical from. It can be found by numerical optimization (Kwong, et al., 1996). ANFIS is a suitable hybrid numerical optimization method adopted in this research for building the inverse model.

Let the general nonlinear model of the plant be represented as

$$y\left(k\right)_{ref} = f\left(x(k), u(k)\right) \tag{9}$$

where $u(k)$ is plant current input, $y\left(k\right)_{ref}$ is the plant's output at the sample time and the function f represents the nonlinear mapping of the neuro-fuzzy model.

The inputs of the estimated model are given by plant's measured input and output data pairs (see figure 5).

$$x(k) = \left[y(k), \bullet\bullet\bullet, y\left(k-n_y\right), u(k) \bullet\bullet\bullet, u\left(k-n_u\right) \right]^T \tag{10}$$

The objective of inverse control is to compute for the current state $x(k)$ the control input, $u(k)$, such that the system's output is equal to the desired (reference) output $r(k)$. The dynamic order of the system is represented by the number of lags n_u and n_y.

This can be achieved if the process model (4) can be inverted according to:

$$u(k) = f^{-1}\left(x(k), y(k)_{ref}\right) \quad (11)$$

An objective function for the process can be defined as

$$J(u(k)) = \left(y(k)_{ref} - f(x(k), u(k))\right)^2 \quad (12)$$

The minimization of J with respect to $u(k)$ gives the control corresponding to the inverse function. This approach directly extends to MIMO systems.

This research is using ANFIS-TSK modelling, considering a TSK model with the following input-output data rules

$$R_i : IF\ y(k)\ is\ A_{i1}\ AND \ldots AND\ y(k-n_y)\ is\ A_{iny} \quad (13)$$

$$AND\ u(k-1)\ is\ B_{i2}\ AND \ldots AND\ u(k-n_u)\ is\ B_{inu}$$

$$THEN\ y_i(k) = \sum_{j=1}^{n_y} a_{ij}(k-j) + \sum_{j=1}^{n_u} b_{ij} u(k-j) + c_i$$

Where

i = 1, ..., k are the rules, A_n B_n, are fuzzy sets and a_{ij}, b_{ij}, c_i are crisp consequent parameters.

Denote the antecedent variables, that is, the lagged outputs and inputs (excluding $u(k)$), by:

$$x(k) = \left[y(k), y(k-1), \bullet\bullet\bullet, y(k-n_y)\right], u(k-1), u(k-n_u) \quad (13b)$$

The output $y(k)$ of the model is computed by the weighted mean formula:

$$y(k) = \frac{\sum_{i=1}^{k} \beta_i(x(k)) y_i(k)}{\sum_{i=1}^{k} \beta_i(x(k))} \quad (14)$$

Where β_i is the degree of fulfilment of the antecedent given by

$$\beta_i(x(k)) = \mu_{A_{i1}}(y(k)) \ AND \ldots AND \ \mu_{A_{in_y}}\left(y\left(k-n_y\right)\right) \ AND$$

$$\mu_{B_{i2}}(u(k-1)) \ AND \ldots AND \ \mu_{B_{in_u}}\left(u\left(k-n_u\right)\right) \quad (15)$$

The consequent part of equation (14) is given by

$$y_i(k) = \sum_{j=1}^{n_y} a_{ij}(k-j) + \sum_{j=1}^{n_u} b_{ij}u(k-j) + c_i \quad (16)$$

As the antecedent of equation (14) excludes the current input term, $u(k)$, the model output equation (16) contains $u(k)$ term. To see how to demonstrate that, degree of fulfilment can be normalize which deals with the controller rule base.

$$\lambda_i(x(k)) = \frac{\beta_i(x(k))}{\sum_{j=1}^{k}\beta_i(x(k))} \quad (17)$$

Substituting (9) and equation (11) into equation (8), one can have

$$y(k) = \sum_{i=1}^{k}\lambda_i(x(k))\left[\sum_{j=1}^{n_y} a_{ij}(k-j) + \sum_{j=1}^{n_u} b_{ij}u(k-j) + c_i\right] + \quad (18)$$

$$\sum_{i=1}^{k}\lambda_i(x(k))b_{i1}u(k)$$

Equation (18) can be written in general terms as:

$$y(k) = g(x(k)) + h(x(k))u(k) \quad (19)$$

The goal of the control is that the output,

$$y(k) = y(k)_{ref}. \quad (20)$$

The corresponding input in terms of equation (20) can be obtained as

$$u(k) = \frac{y(k)ref - g(x(k))}{h(x(k))} \quad (21)$$

Substituting for $g(x(k))$ and $h(x(k))$from equation (17) into equation (20), the inverse-model control law will be given as

$$u(k) = \frac{y(k)_{ref.} - \sum_{i=1}^{k} \lambda_i(x(k)) \left[\sum_{j=1}^{n_y} a_{ij}(k-j) + \sum_{j=1}^{n_u} b_{ij} u(k-j) + c_i \right]}{\sum_{i=1}^{k} \lambda_i(x(k)) b_{ij}} \tag{22}$$

Genetic Algorithm Based Neuro-fuzzy controller

For Genetic- Adaptive- Neuro-Fuzzy Inference System (GANFIS) to work in unison, embedded hybridization has to be employed to facilitate their function. The ANFIS controller receives fuzzy inputs via the NN, where it is processed to produce fuzzy output(s) while the genetic algorithm tunes the fuzzy sets which are used in rule base formation (Figure 4). The control system has an input, $u(k)$ and an output, y. The ANFIS controller consists of the fuzzification phase which is achieved using Fuzzy logic to create fuzzy sets that are required for the rule base formation while the inference phase involves using neural network (NN) to infer the inputs which are fuzzy to provide the required input weights for updating the system data. The deffuziffication phase is the weighted average of the NN outputs, thus producing a crisp value as the controller output, $u(k)$.

The ANFIS controller is formulated using GA approach where the inputs membership functions of the controller parameters are initially randomized, tuned and optimized simultaneously. The fitness of the corresponding ANFIS is formulated on the basis of the response of the plant model via a predefined performance function see figure 6, (Seng, et al.,1999).

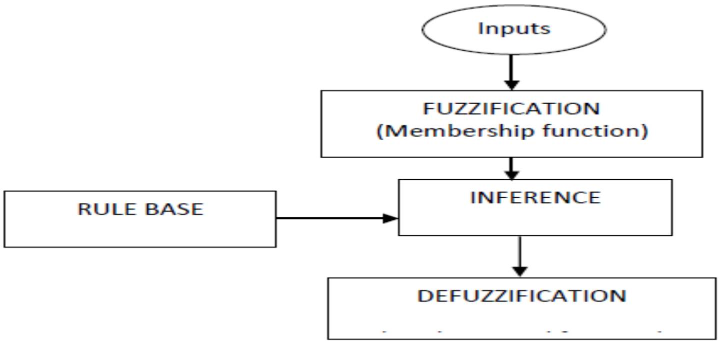

Figure 6: Block diagram of TS fuzzy model **(**Ribhan, *et al.*, 2008)

$$\varepsilon = \frac{1}{2}\sum_{i}^{N}\left(y_{sp}-y_i\right)^2 \qquad (23)$$

The error is generated by subtracting the plant on-line output (y) from the plant set-point (y_{sp}) which is mathematically represented as equation 8.

The controller block diagram in figure 8 shows the determination of initial error for controller.

In this research, Takagi and Sugeno-Kang (TSK) fuzzy model is adopted; the structure of TSK fuzzy model consists of three main components: antecedent part, rule base and consequent part. Input variables are represented by membership functions as in standard fuzzy system. In the consequent part, mathematical functions are used instead of membership functions. The structure can be seen as a combination of linguistic and mathematical modelling (equation 5).

From equation (1), where $x(t)\in R^n$ and $u(t)\in R^m$ are the system state and input vectors. The TSK model of the system is represented by the system's state variables by a control rule

IF X_1 is A_1 and $\bullet\bullet\bullet$ and X_n is A_n Then

$$U = p_1 x_1 + \bullet\bullet\bullet + p_n x_n + p_0 \qquad (24)$$

Where

$X_i = \left[x_1, x_2 \bullet\bullet\bullet x_n\right]^T$ are the universe of discourse of the input/output data of the system?

$A_i = \left[A_1, A_2 \bullet\bullet\bullet A_n\right]^T$ are the membership functions of the antecedent part?

$p_i = \left[p_0, p_1, p_2 \bullet\bullet\bullet p_n\right]^T$ are the real number of the consequent part and $i = 1, 2, \bullet\bullet\bullet n$ is the number of variables in the data.

The activation generalized bell (gbell) membership function employed for the fuzzification process, is

$$\mu_{A_i}(x_i) = \frac{1}{1+\left(\frac{x_i - c_{A_i}^{x_i}}{a_{A_i}^{i}}\right)^{2b}} \tag{25}$$

Where

x_i are points on the universe of discourse X ,

$c_{A_i}^{x_i}$ is the center of membership function $\mu_{A_i}(x_i)$,

$a_{A_i}^{i}$ is the width of membership function $\mu_{A_i}(x_i)$ and

b is the gbell slop membership function slope.

The following important characteristics of the membership functions contained within fuzzification are as follows:

Since membership functions divide the Universe of Discourse (UoD) into sections, it is important that the membership functions cover the entire UoD. This ensures that every possible crisp input has an associated linguistic term which can be used for processing within the Inference Engine.

Linguistic terms reflect the plant operator's analysis of the input output space and description for a range of values of the UoD. The flexibility of incorporating existing knowledge into the ANFIS controller makes it easier for the design of the ANFIS-GA controller.

The first issue that arises in a GA optimization is coding of the parameter set. There are several ways to encode the parameter set for optimizing fuzzy logic. For example, both rule base as well as the membership function parameters can be encoded in one GA representation (Seng, *et al.*, 1999 and Ribhan, *et al.*,2008). Similarly, one could use different representations for membership functions and rule base. In this paper, one single GA chromosome represents the parameters of membership functions for inputs. A bell shaped membership function is characterized as shown in equation (17) by mean or center (c) and variance or width (a) and a slope (b).

The aim of genetic algorithms is to use simple representations to encode complex structures and simple operations to improve these structures. The gbell MF equation 23 is considered as the objective function of this research. The three variables a, b and c are taken as the genetic population individuals that are optimized, based on figure 4 and equation 17, the SSCN ANFIS data are subjected to Genetic algorithm optimization by Genetic program based on the genetic algorithm shown in figure 7.

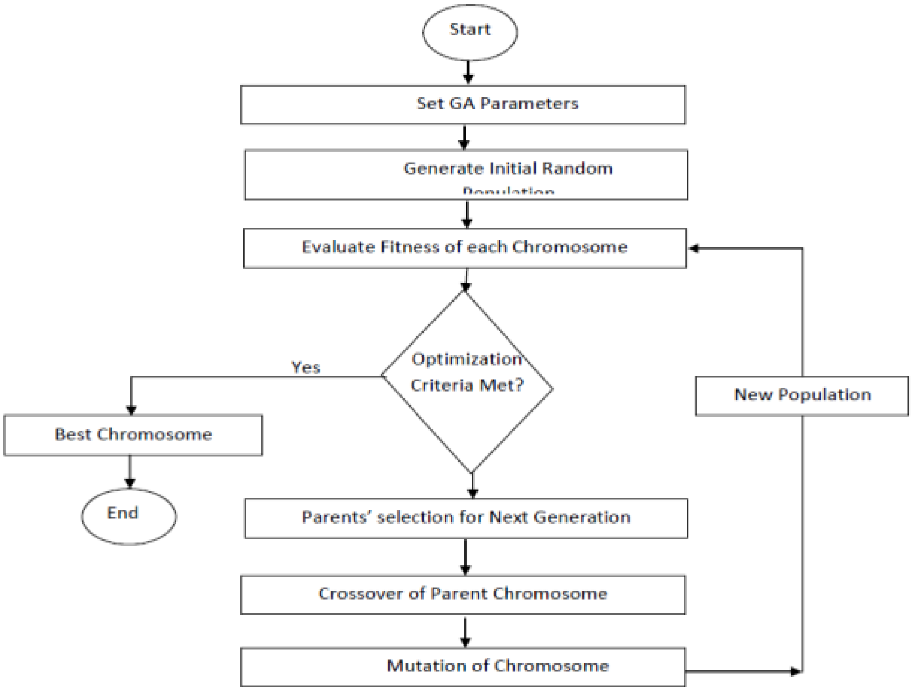

Figure 7: Flowchart of Genetic algorithm (Sabbir, 2008).

The embedded GA based ANFIS controller in the Savannah Sugar Company thermal power plant simulink is shown in figure 8.

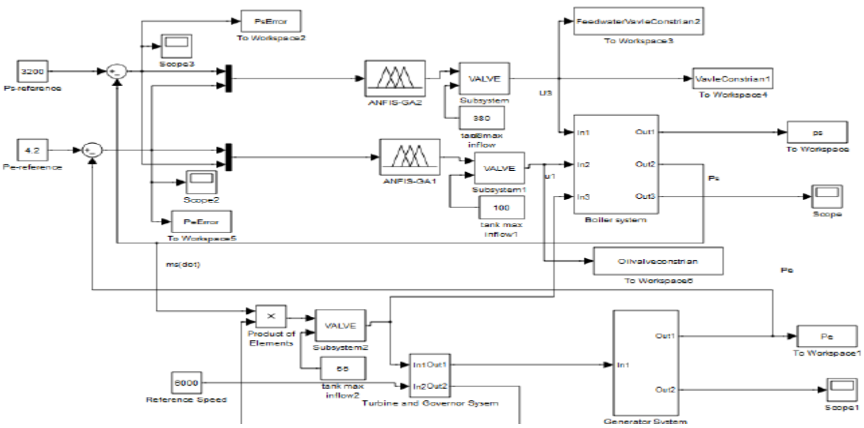

Figure 8: SSCN Thermal Power Plant GA based ANFIS controlled Simulink.

Result and Discussion

In order to evaluate the overall controller efficiency, after tuning of the MF parameters, 200 random test data is generated with their fitness values. The Optimal values are obtained from 100 generations as the fitness versus generation plot shows in Figure 10.

The fuzzy rule base of the GA based ANFIS controller is achieved by using the optimized ANFIS controller Gaussian-bell shaped MF parameters. The optimized parameters shown in Figures 11, 12 and 13 are the predefined data base used in training the FIS in the Fuzzy toolbox, thus producing the required GA based ANFIS controller that is embedded in the SSCN simulink model for plant control.

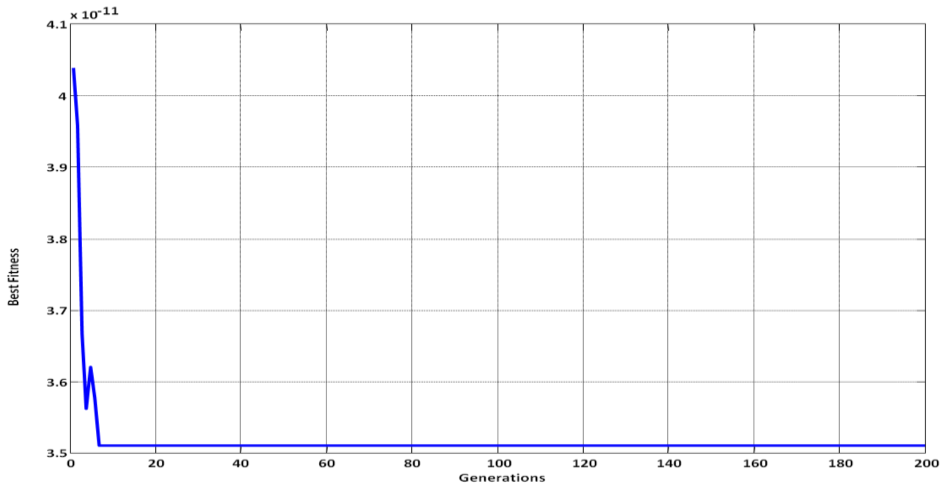

Figure 10: SSCN Boiler Output, Gaussian Bell Membership Function parameter learning by Genetic Algorithm

Function parameter learning by Genetic Algorithm
The best parent of the GA is a = 3458kPa, b = 1564kPa, and c = 3194kPa
Elapsed time is 21.323565 seconds.

The GA optimized individual chromosome parameters of ‘a’, ’b’ and ‘c’ of the antecedent part of the input membership functions are shown in figures 11, 12 and 13 respectively

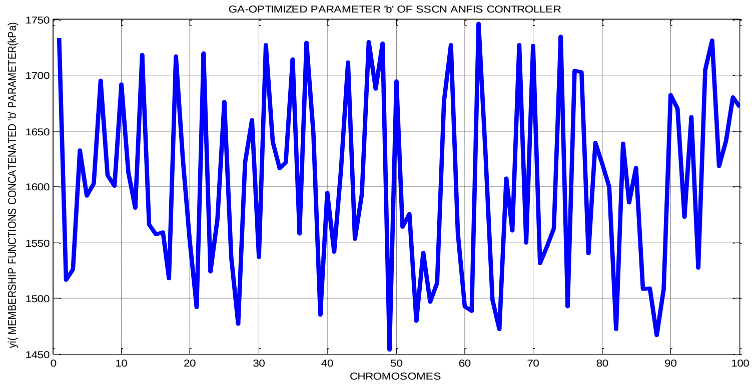

Figure 11: Concatenated width ('a') parameter of Input gbell Membership Functions

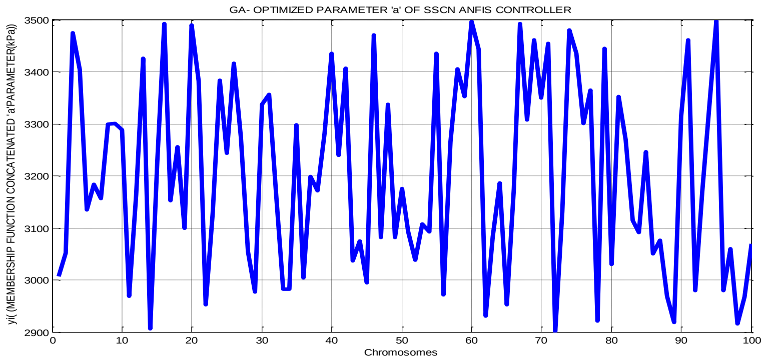

Figure 12: Concatenated slope ('b') parameter of Input gbell Membership Functions

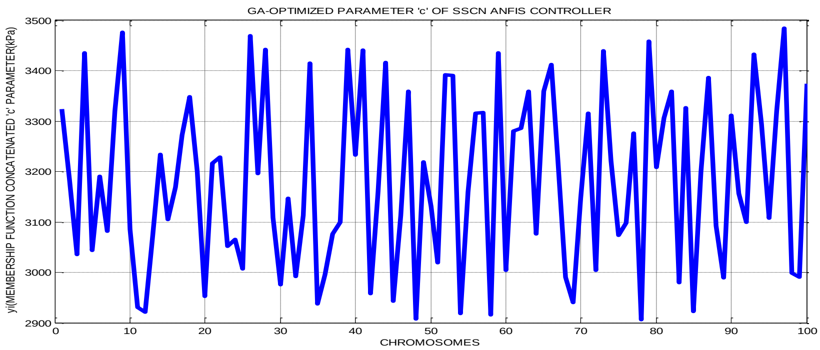

Figure 13: Concatenated centre ('c') parameter of Input gbell Membership Functions

Simulation of SSCN thermal power plant simulink with GA based controller produced the controlled steam-to-tubine with acceptable deviation from the plant's set-point as shown in figure 14.

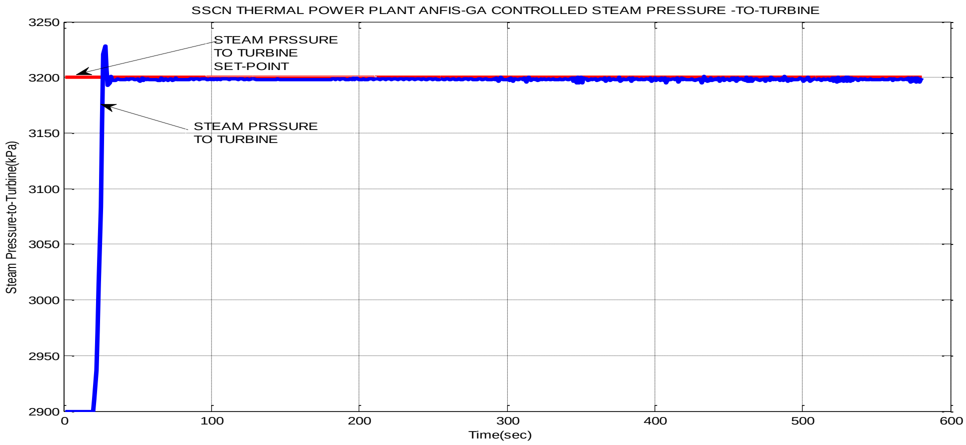

Figure 14: ANFIS-GA controlled steam-to-turbine of SSCN thermal power plant

GA based ANFIS controller control tracking of the steam pressure to turbine which is achieved by changing semi-points at different times, showed that the controller was able to control the steam to turbine adequately with much deviation from set-point as shown in figure 15

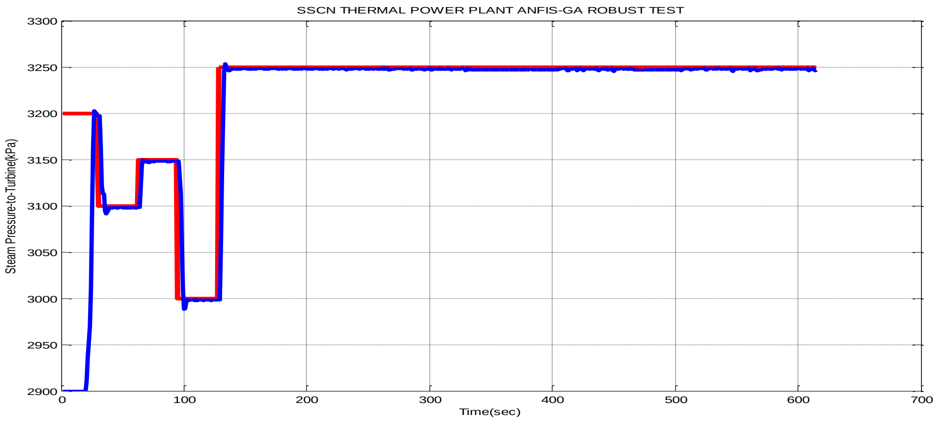

Figure 15: SSCN Thermal Power Plant GA based ANFIS Controller Robust test

To verify the advantage of the GA based ANFIS controller over ANFIS controller, it be beneficial to produce ANFIS controller boiler output control tracking as shown in figure 16. Here the controlled steam to turbine has significant deviation from set-point than Ga based Controller

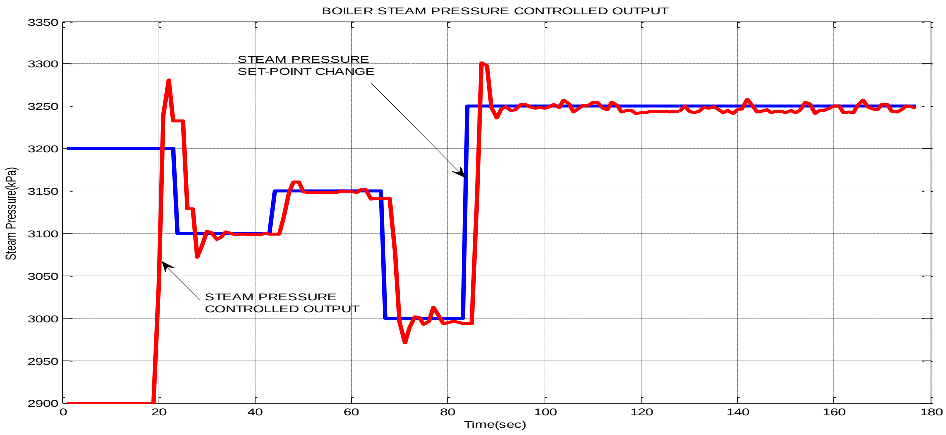

Figure 16: SSCN Thermal Power Plant ANFIS Control Set Point Tracking

The SSCN Electrical power output generated by GA based ANFIS controller is as shown in figure 17

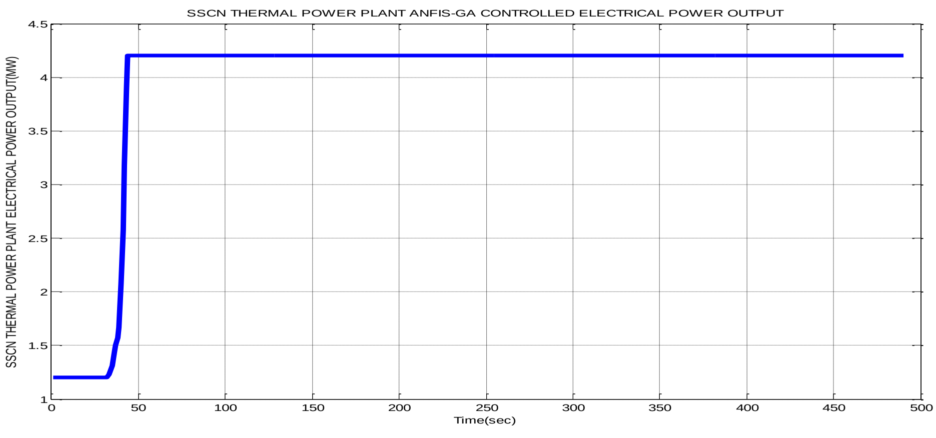

Figure 17: SSCN Thermal Power Plant GA Based ANFIS Controlled Electrical Power

Conclusion

To facilitate this research, mathematical models were developed to represent the steam pressure and electrical power generated by the power system. The models were used for dynamic simulation studies with data taken from the existing power plant. This provides flexibility in the research work whereby studies were carried out to improve the performance and efficiency of the existing plant.

The fuzzy rule base of the ANFIS-GA controller is achieved by using the optimized Gaussian-bell shaped MF parameters of the power plant's inputs. The optimized parameters formed the predefined data base which is used in training a FIS in the Fuzzy toolbox where rules are automatically generated for the required ANFIS-GA controller which is embedded in the SSCN simulink model for simulation.

Applying the set-point pressure (3200 kPa) of the SSCN power plant, simulation of the power plant showed that boiler steam pressure to turbine will generate the required power plant's designed electrical power. The embedded ANFI-GA controller into the SSCN simulink model shows that there is stable control at the start of operation to the end of each shift's operation. This controlled steam pressure to turbine results in stable electrical power generation for a span of 1.2MW to 4.2MW.

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